



COMP9321:

Data services engineering

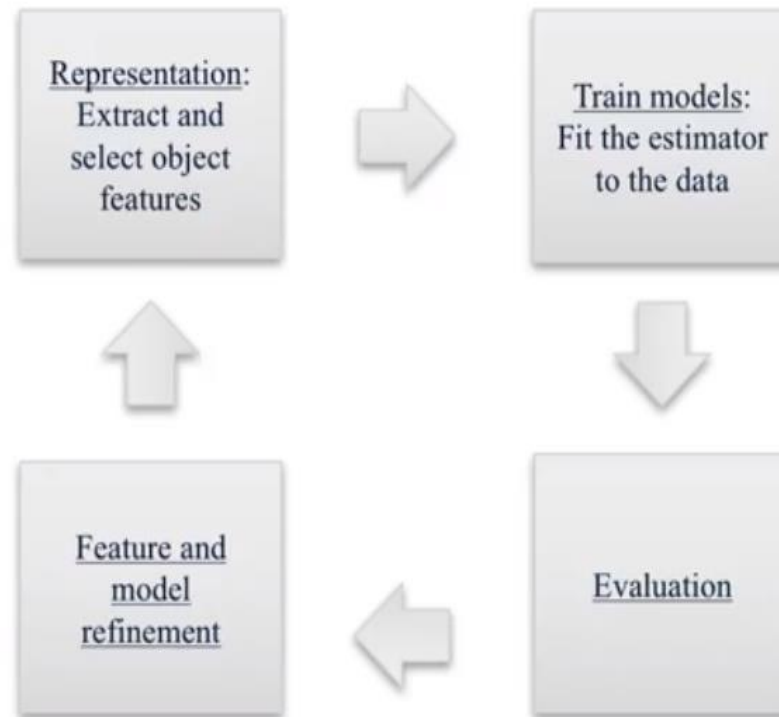
Week 10: More About Data Analytics (Classification recap, Regression, and Clustering)

Semester 2, 2018

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Refresher

Represent / Train / Evaluate / Refine Cycle



k-NN Refresher

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

fruits = pd.read_table('fruit_data_with_colors.txt')

X = fruits[['height', 'width', 'mass', 'color_score']]
y = fruits['fruit_label']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

knn = KNeighborsClassifier(n_neighbors = 5)
knn.fit(X_train, y_train)
print("Accuracy of K-NN classifier on test set: ", knn.score(X_test, y_test))

example_fruit = [[5.5, 2.2, 10, 0.70]]
print("Predicted fruit type for ", example_fruit, " is ", knn.predict(example_fruit))
```

Accuracy with Imbalanced Classes

- Suppose you have two classes:
 - The positive class
 - The negative class
- Out of 1000 randomly selected items, on average:
- One item belong to the positive class
- The rest of items (999 of them) belong to the negative class
- The Accuracy will be

$$\text{Accuracy} = \frac{\text{\#correct predictions}}{\text{\#total instances}}$$

Accuracy with Imbalanced Classes

- When you build a classifier to predict the items (positive or negative), you may find out that the accuracy on the test set is 99.9%.
- Be aware that this is not an actual presentation of how good your classifier is.
- For comparison, if we have a “dummy” classifier that does not consider the features at all but rather blindly predicts according to the most frequent class

Accuracy with Imbalanced Classes

- If we use the same dataset mentioned in the previous slide (the 1000 data instance with 999 negative and 1 positive). What do you think the accuracy of the dummy classifier would be?

Answer:

$$\text{Accuracy}_{\text{Dummy}} = 999/1000 = 99.9\%$$

- Hence the accuracy alone sometime not a good metric to measure how good the model is

Precision and Recall

Precision

Precision attempts to answer the following question:

What proportion of positive identifications was actually correct?

Precision is defined as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

TP: True Positive

FP: False Positive

FN: False Negative

Recall

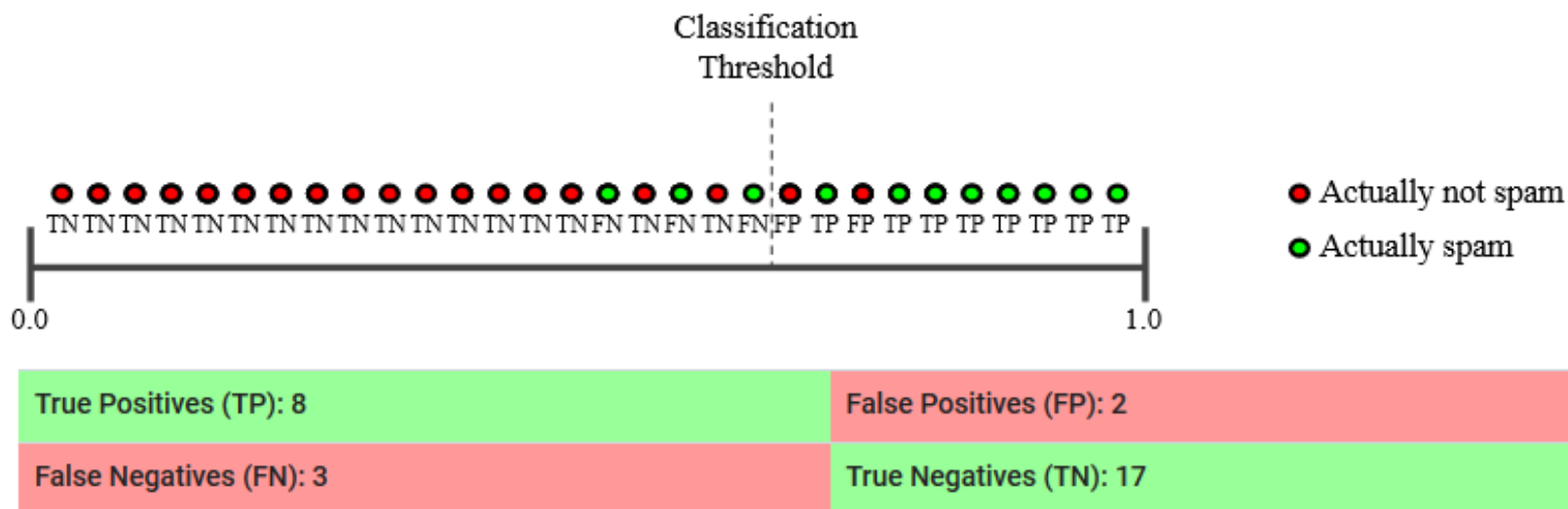
Recall attempts to answer the following question:

What proportion of actual positives was identified correctly?

Mathematically, recall is defined as follows:

$$\text{Recall} = \frac{TP}{TP + FN}$$

Precision and Recall



Precision measures the percentage of **emails flagged as spam** that were correctly classified—that is, the percentage of dots to the right of the threshold line that are green

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{8}{8 + 2} = 0.8$$

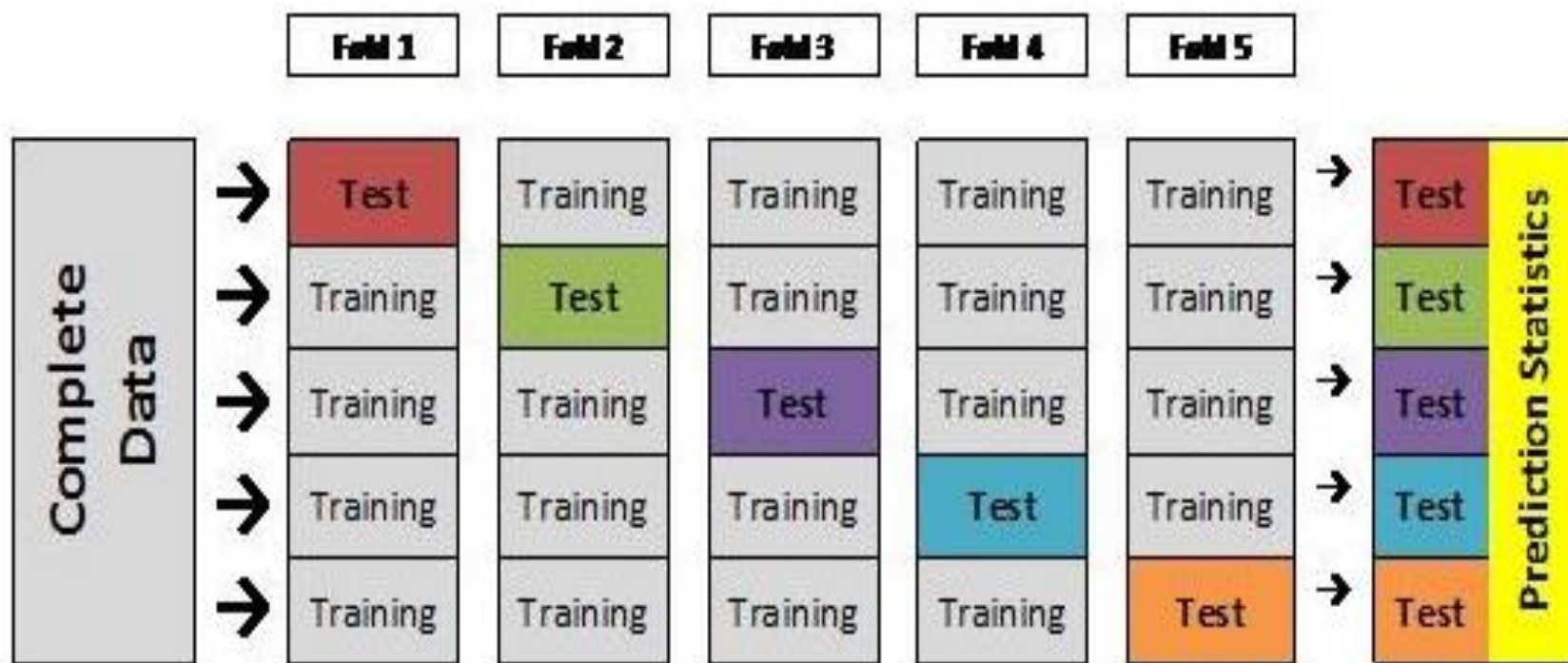
Recall measures the percentage of **actual spam emails** that were correctly classified—that is, the percentage of green dots that are to the right of the threshold line

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{8}{8 + 3} = 0.73$$

Cross-validation

- Cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample.
- The procedure has a single parameter called k that refers to the number of groups that a given data sample is to be split into. As such, the procedure is often called k -fold cross-validation.
- When a specific value for k is chosen, it may be used in place of k in the reference to the model, such as $k=5$ becoming 5-fold cross-validation.

Cross Validation Examples (5-fold)



Stratified Cross-validation

fruit_label	fruit_name
1	Apple
1	Apple
1	Apple
1	Apple
1	Apple
2	Mandarin
...	...
3	Orange
...	...
4	Lemon
4	Lemon
4	Lemon
4	Lemon
4	Lemon

(Folds and dataset shortened for illustration purposes.)

Example has 20 data samples
= 4 classes with 5 samples each.

5-fold CV: 5 folds of 4 samples each.

Fold 1 uses the first 20% of the dataset as the test set,
which only contains samples from class 1.

Classes 2, 3, 4 are missing entirely from test set and so
will be missing from the evaluation.

Cross Validation Example

Example based on k-NN classifier with fruit dataset (2 features)

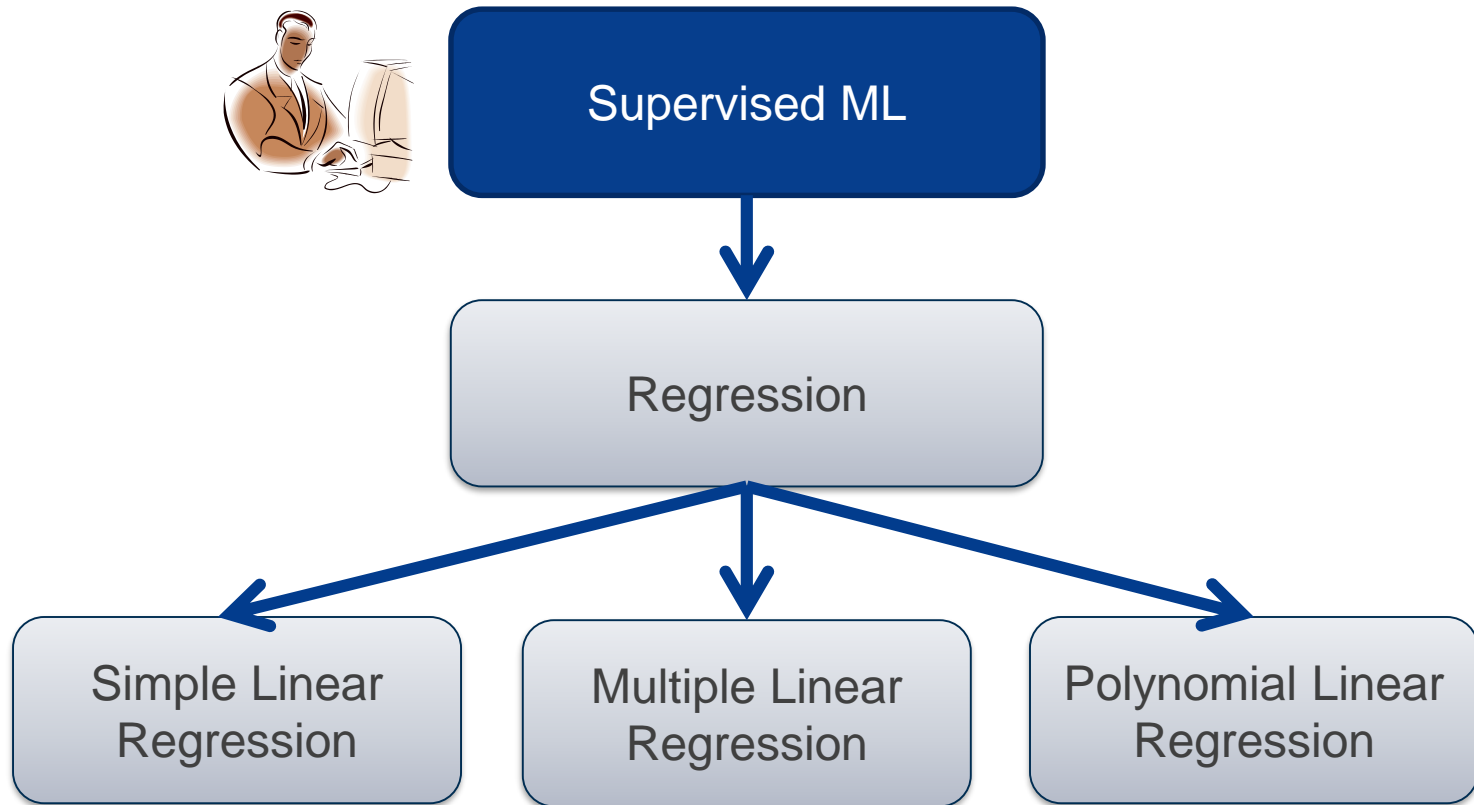
```
In [30]: from sklearn.model_selection import cross_val_score

clf = KNeighborsClassifier(n_neighbors = 5)
X = X_fruits_2d.as_matrix()
y = y_fruits_2d.as_matrix()
cv_scores = cross_val_score(clf, X, y)

print('Cross-validation scores (3-fold):', cv_scores)
print('Mean cross-validation score (3-fold): {:.3f}'
      .format(np.mean(cv_scores)))
```

```
Cross-validation scores (3-fold): [ 0.77  0.74  0.83]
Mean cross-validation score (3-fold): 0.781
```

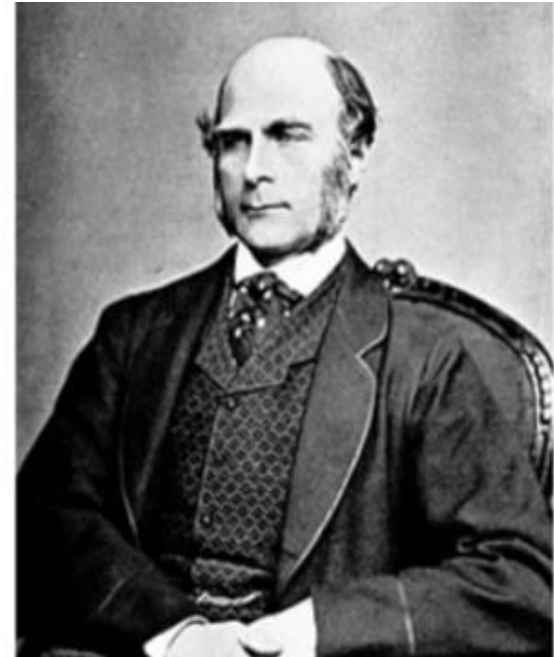
Regression Analysis

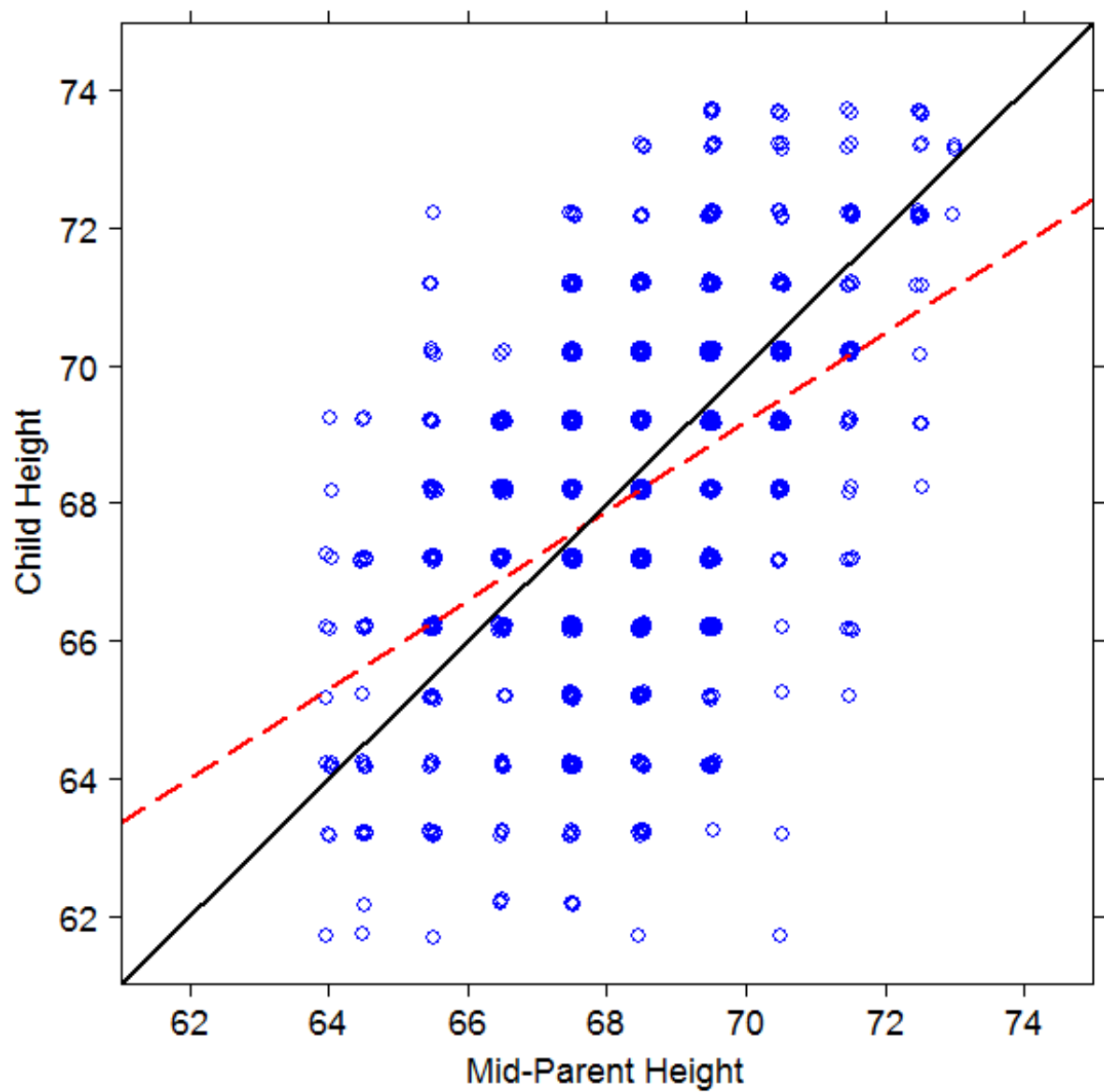


Sir Francis Galton, 1822-1911

Regression Towards Mediocrity in
Hereditary Stature

*Journal of the Anthropological
Institute*, 1886; 15:246-63





Regression Analysis

- A linear Model is a sum of weighted variables that predict a target output value given an input data instance

Example: Predicting housing prices

House features: taxes paid per year (X_{tax}), age in years (X_{age})

$$\text{Predicted price} = 143000 + 100 X_{\text{tax}} - 4000 X_{\text{age}}$$

- So if the house tax per year is 20000, and the age of the house is 60 years then the predicted selling price is:

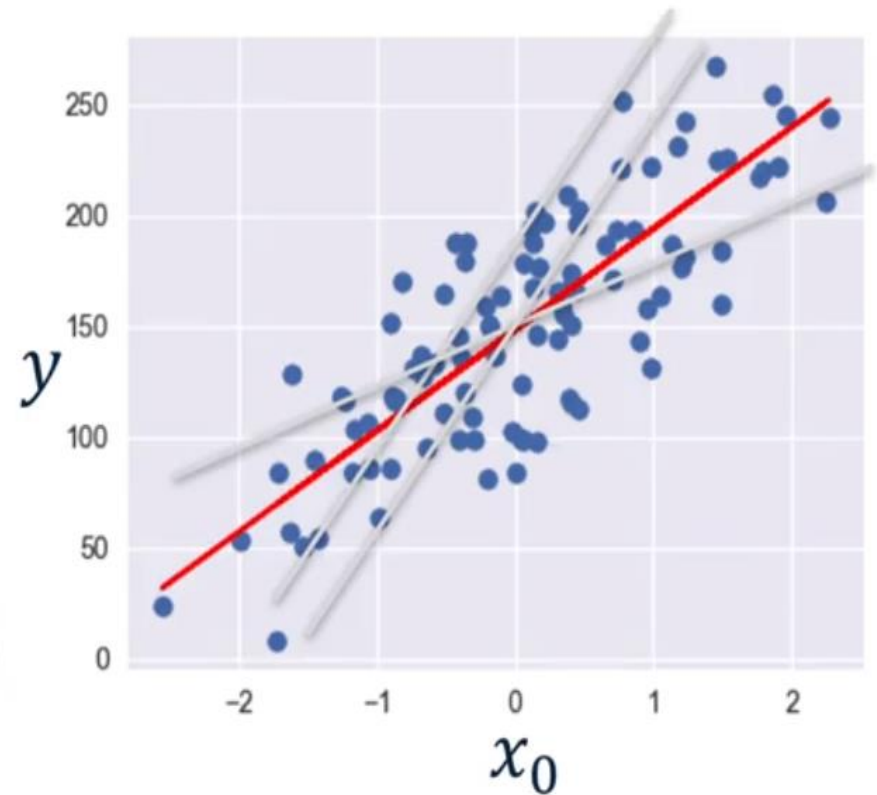
$$\text{Predicted price} = 80000 + 100 \times 20000 - 4000 \times 60 = 1,840,000$$

How Linear Regression Works

Input instance: $\mathbf{x} = (x_0)$

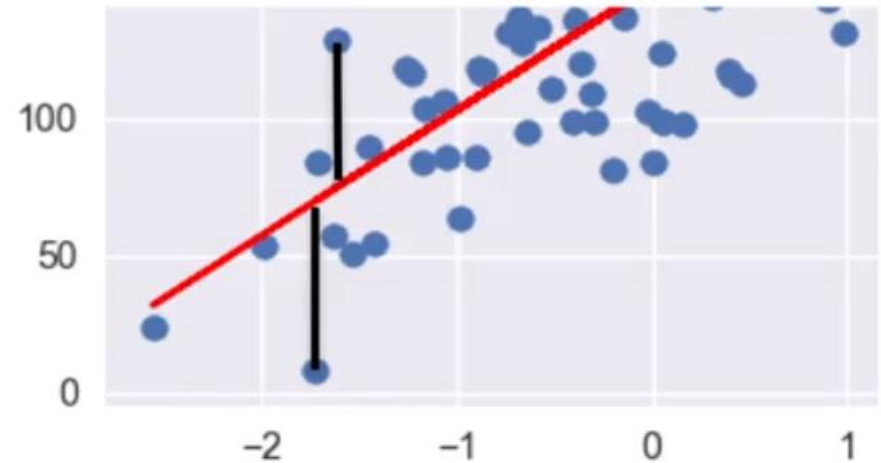
Predicted output: $\hat{y} = \hat{w}_0 x_0 + \hat{b}$

Parameters to estimate: \hat{w}_0 (slope)
 \hat{b} (y-intercept)



Linear Regression (Least-squares)

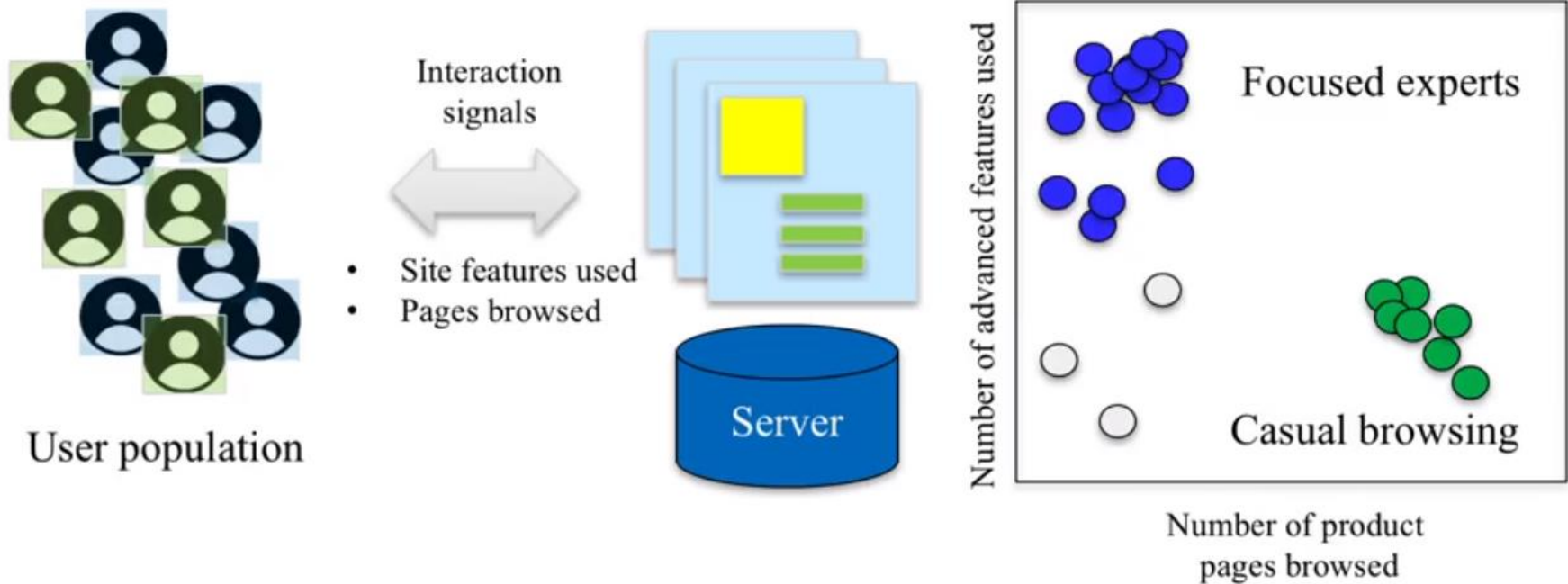
- Finds w and b that minimizes the mean squared error of the model: the sum of squared differences between predicted target and actual target values.
- No parameters to control model complexity.



Unsupervised Learning

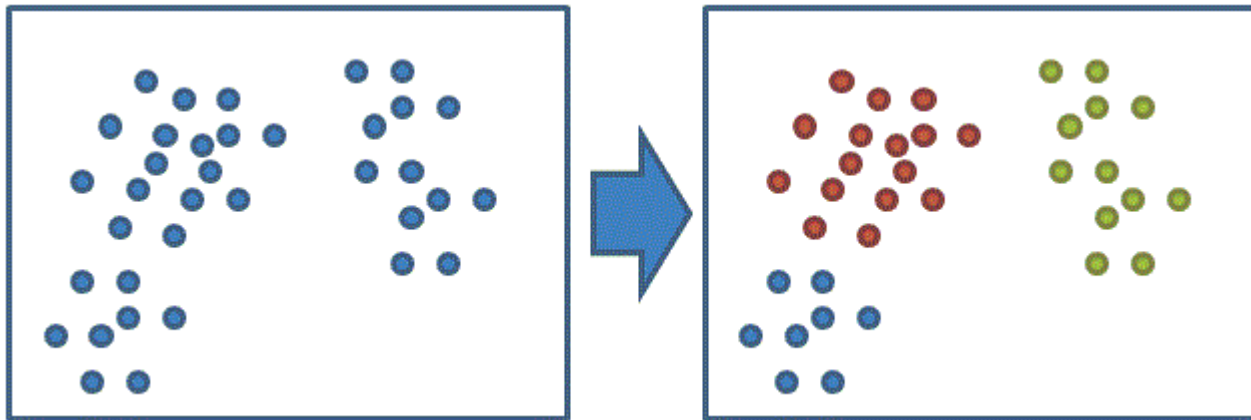
- Unsupervised learning involves operating on datasets without labelled responses or target values.
- The goal is to capture a structure of interest of useful information (e.g., relationships)
- Unsupervised learning good be used in:
 - ☐ Visualizing the structure of a complex dataset
 - ☐ Compressing and summarising the data
 - ☐ Extracting features for supervised learning
 - ☐ Discover groups or outliers

Web Clustering Examples



Clustering

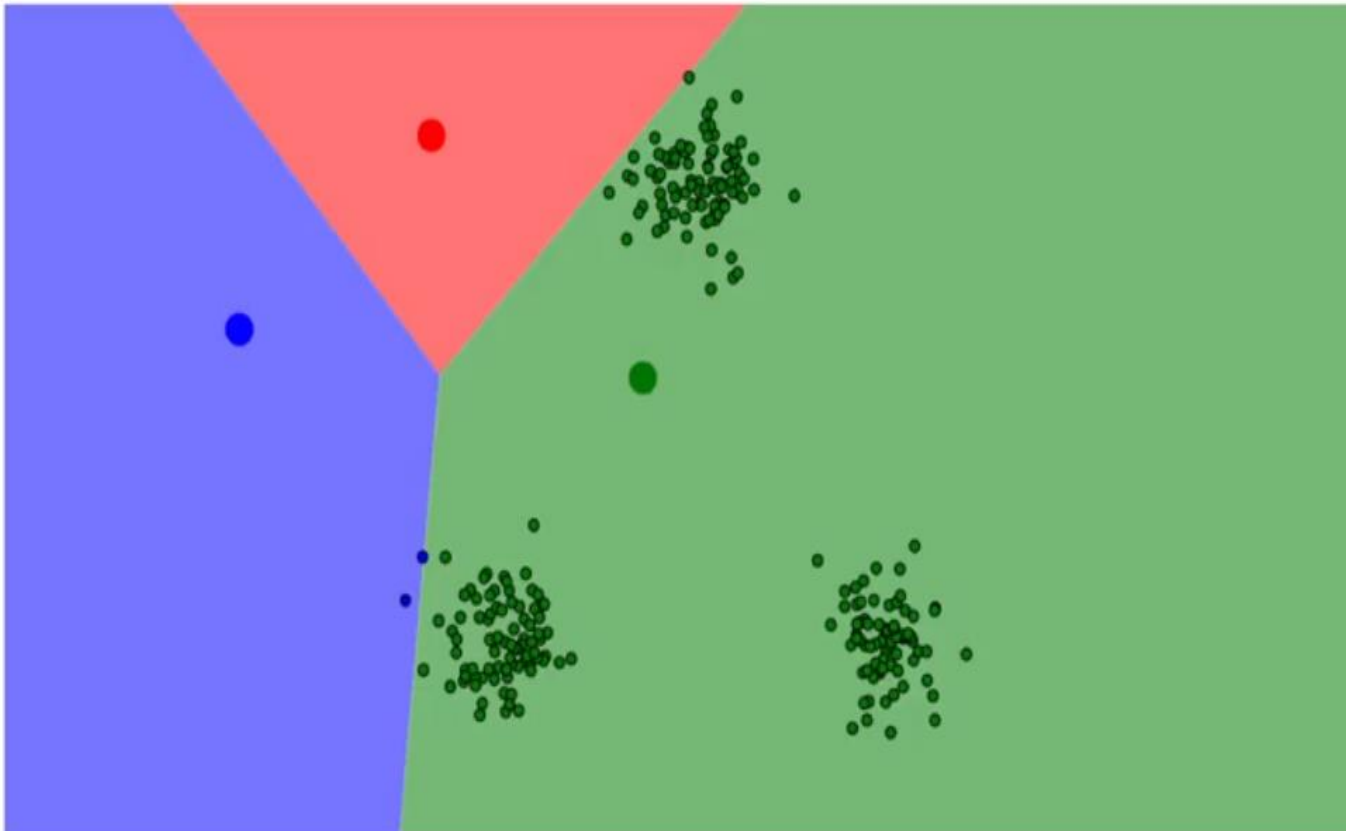
- What is it? Finding a way to group data in a datasets (putting them in clusters)
- Data points within the same cluster should be close or similar in some way.
- Data points in different clusters should be far a way or differ in some way



K-means Clustering Algorithm

- **Initialize:**
 - decide the number of k clusters you want to find.
 - Pick k random points to serve as initial guess of the cluster centres
- **Step A:**
 - Assign each data point to the nearest cluster centre
- **Step B:**
 - Update each cluster centre by replacing it with the mean of all points assigned to that centre (from step A)
- **Iterate:**
 - Iterate over steps A and B until centres converge to a stable solution

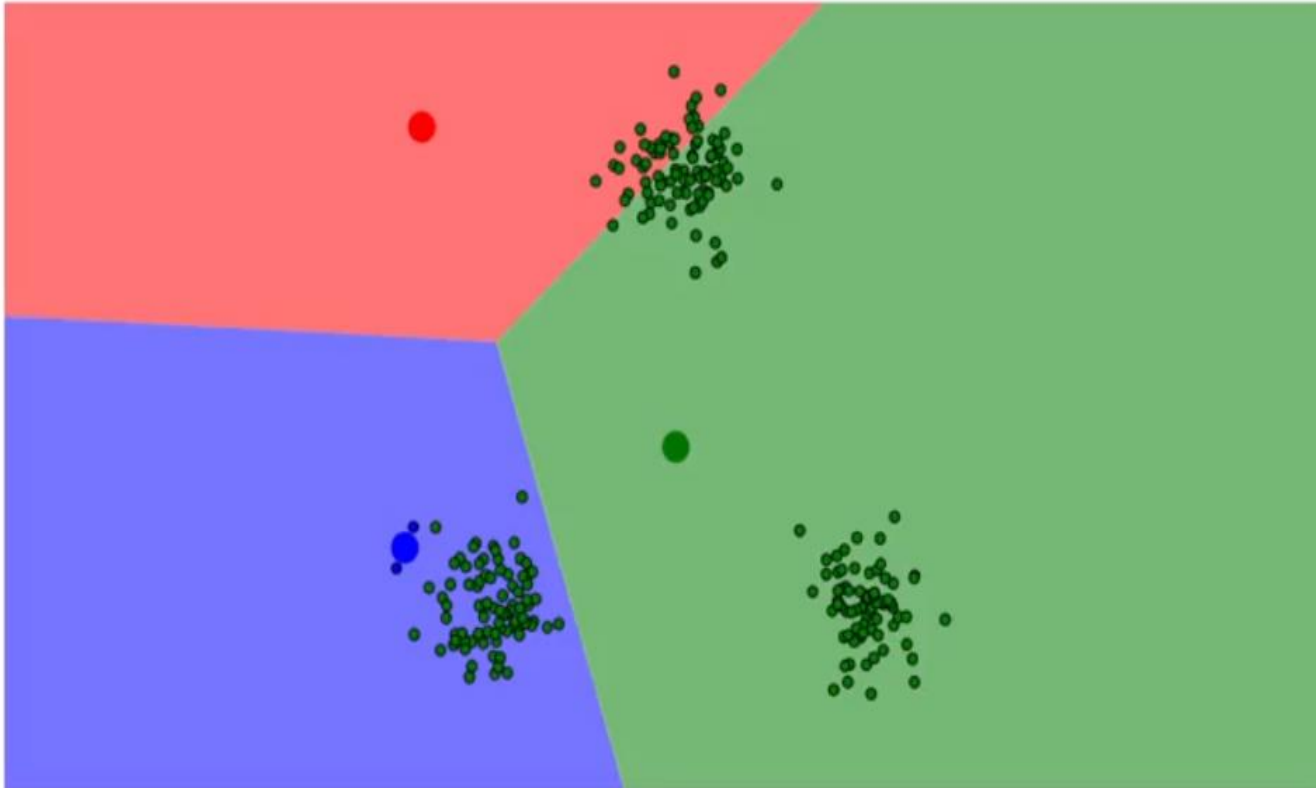
K-means Example: Step 1A



We want three clusters, so three centers are chosen randomly.

Data points are colored according to the closest center.

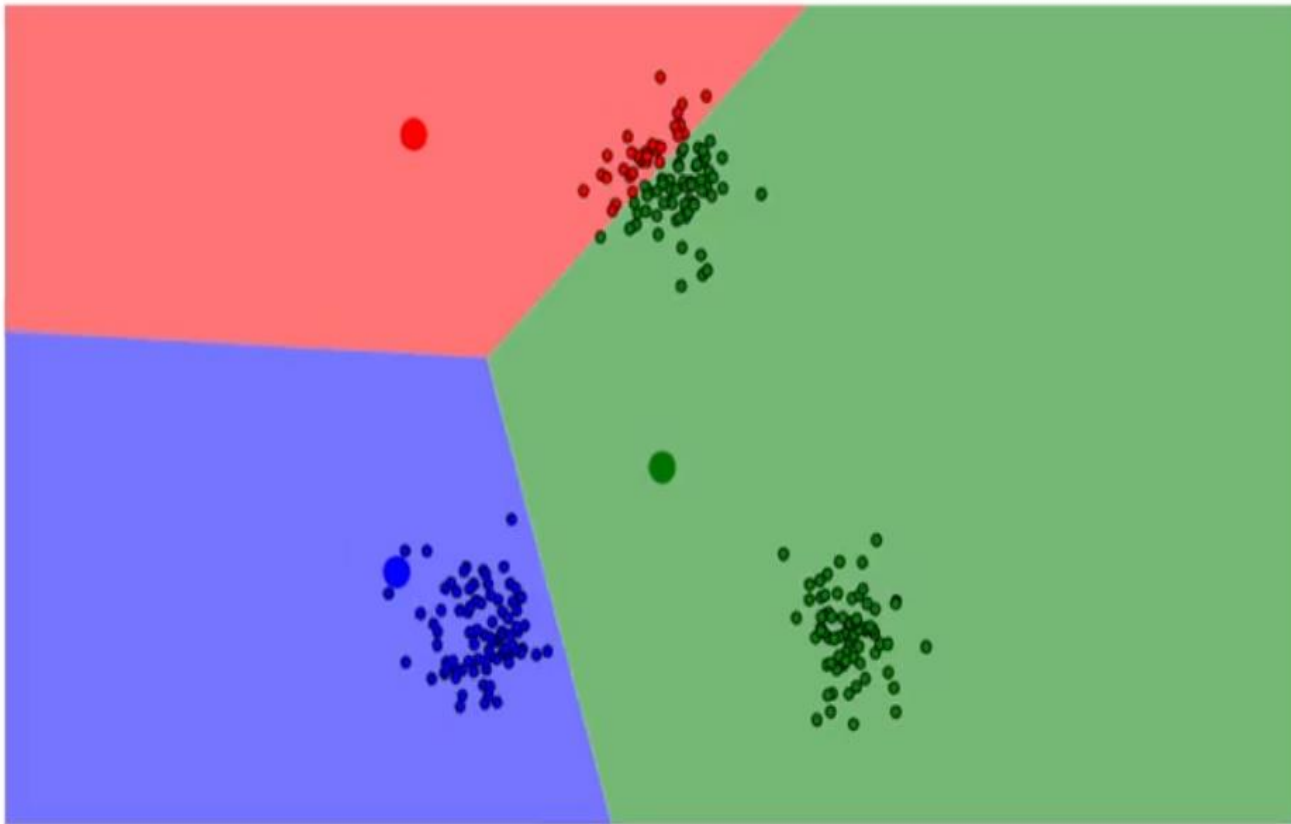
K-means Example: Step 1B



Each center is then updated...

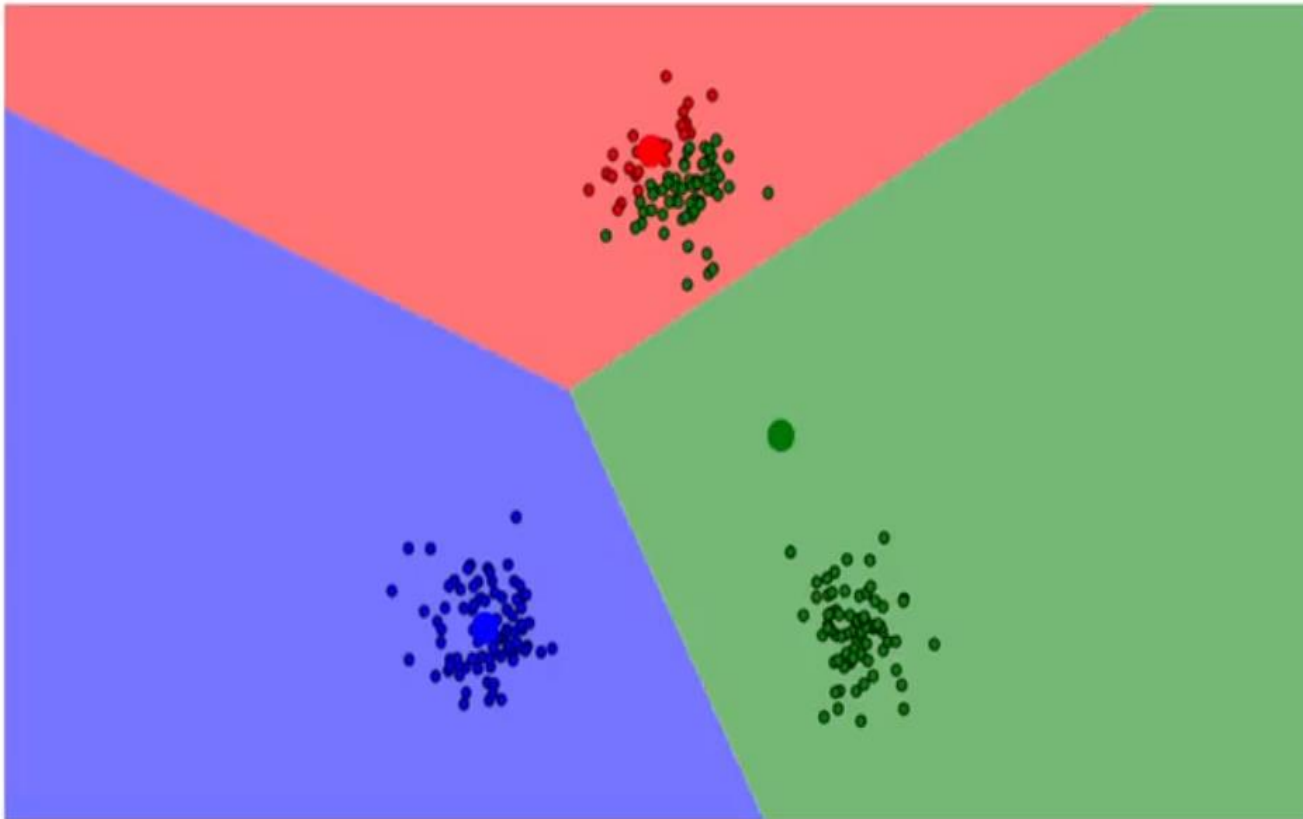
... using the mean of all points assigned to that cluster.

K-means Example: Step 2A

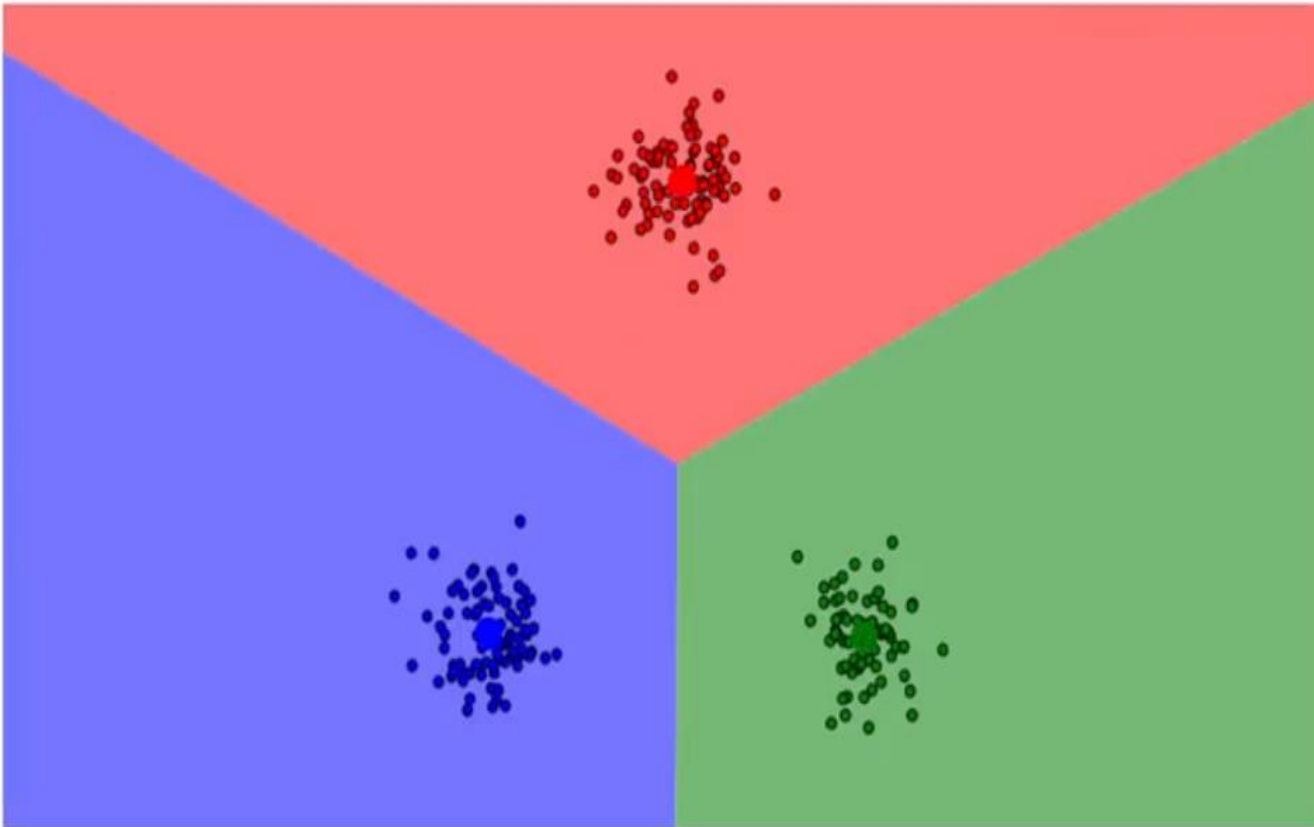


Data points are colored (again) according to the closest center.

K-means Example: Step 2B



K-means Example: Converged



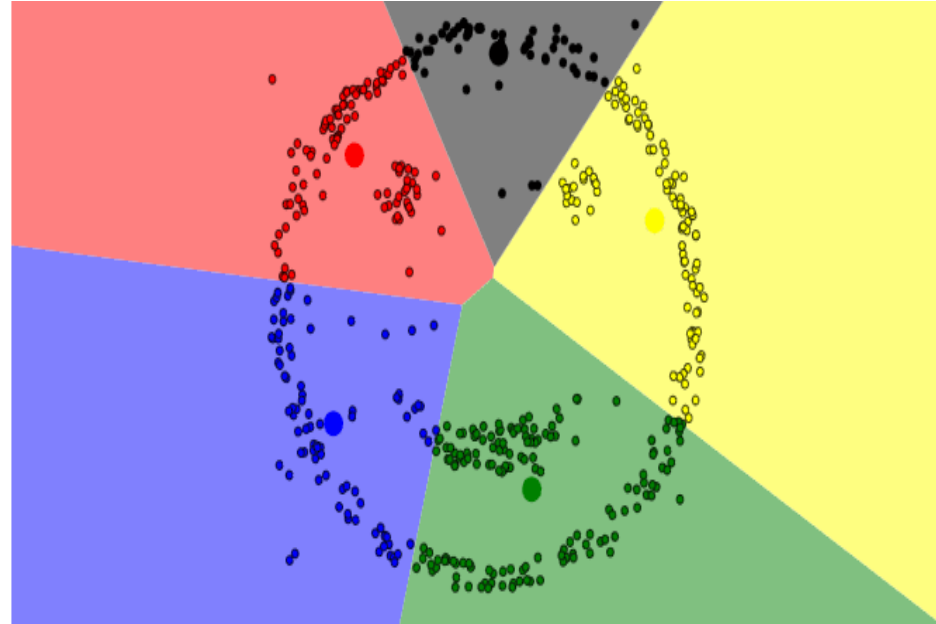
After repeating these steps for several more iterations...

The centers converge to a stable solution!

These centers define the final clusters.

Limitations of k-means

- Sometime the number of clusters is difficult to determine
- Does not do well with irregular or complex clusters.
- Has a problem with data containing outliers



How to Select the Machine Learning Model

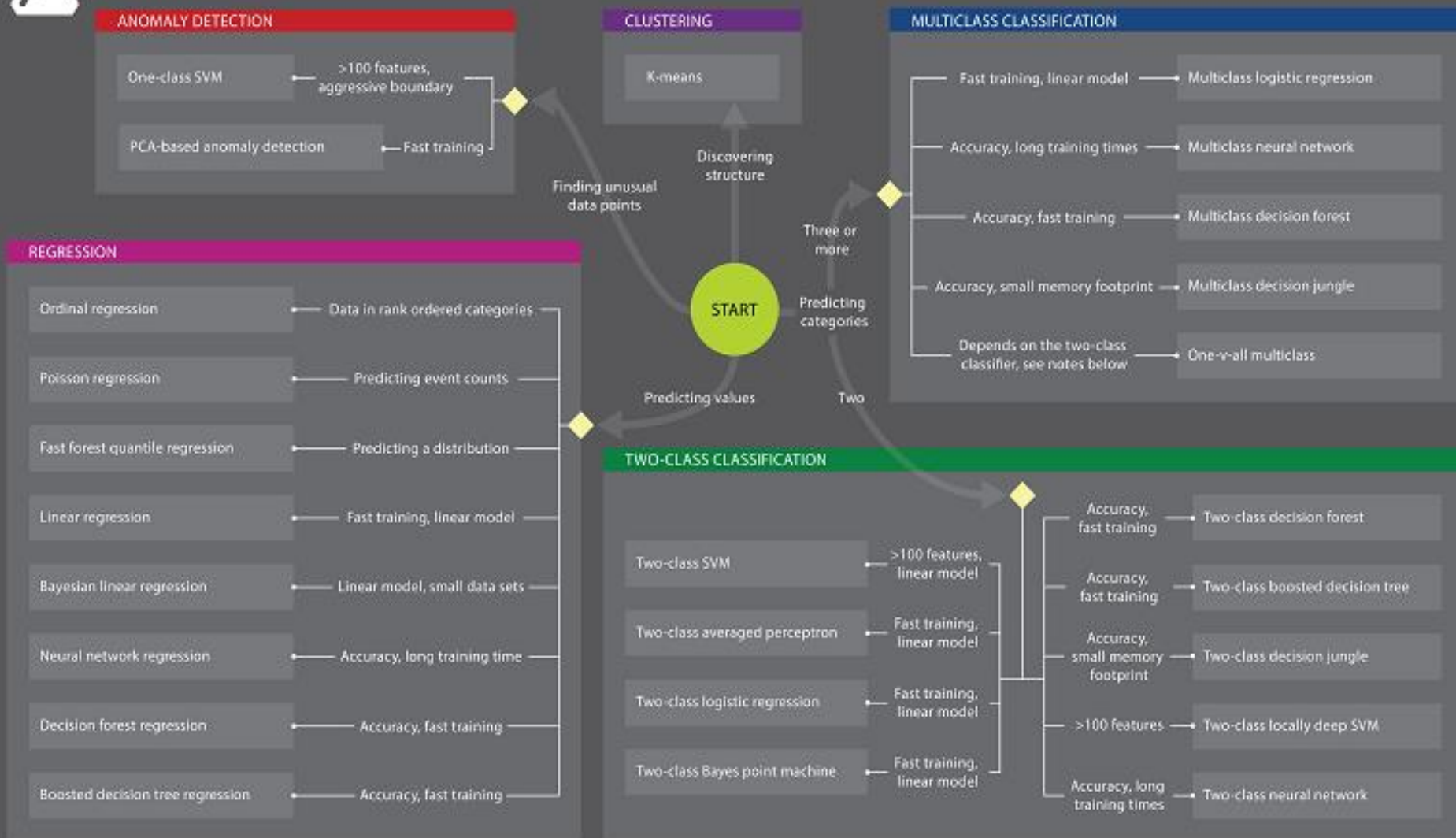
“It depends.”

- It depends on the size, quality, and nature of the data. It depends on what you want to do with the answer. It depends on how the math of the algorithm was translated into instructions for the computer you are using. And it depends on how much time you have.
- Even the most experienced data scientists can't tell which algorithm will perform best before trying them.

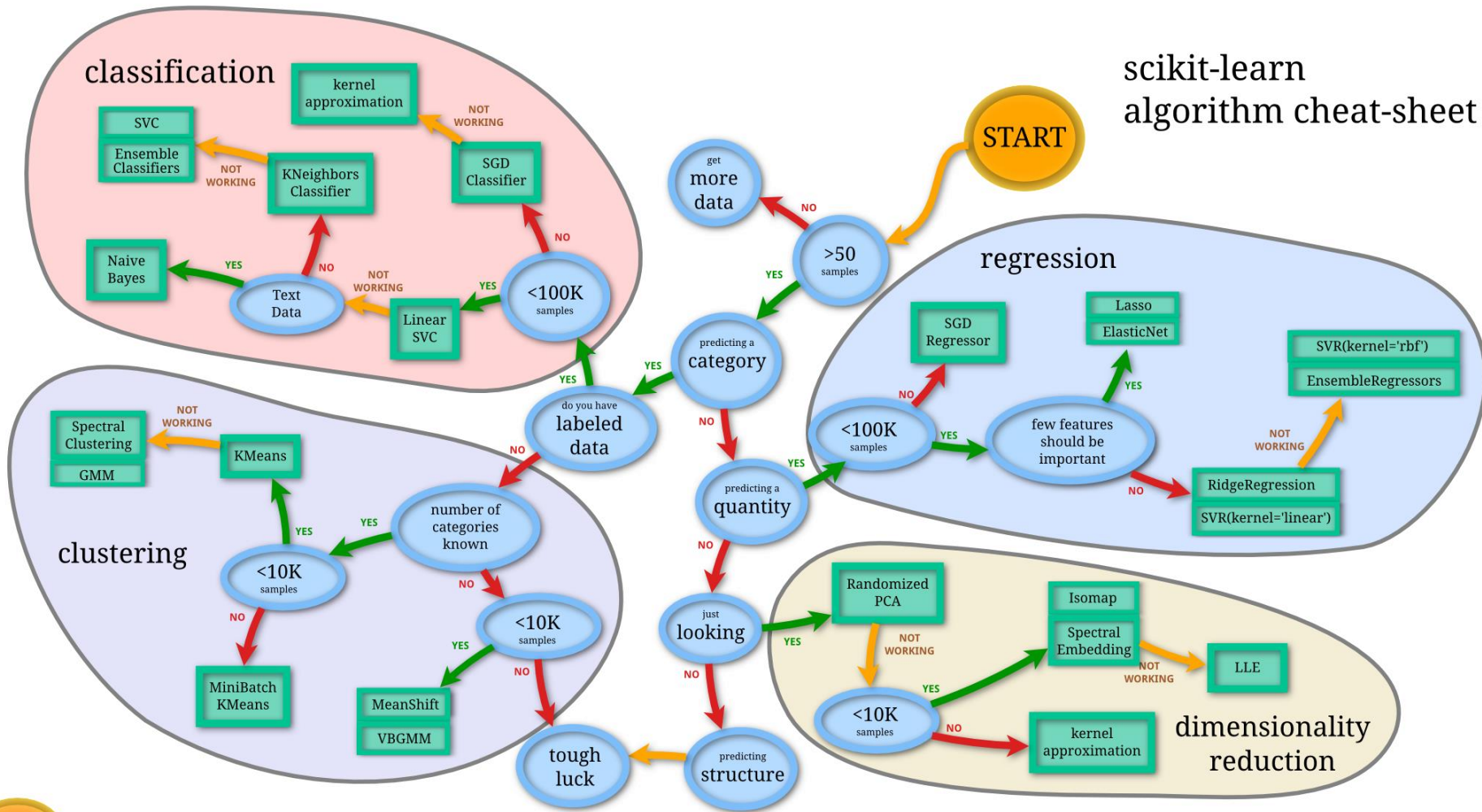


Microsoft Azure Machine Learning: Algorithm Cheat Sheet

This cheat sheet helps you choose the best Azure Machine Learning Studio algorithm for your predictive analytics solution. Your decision is driven by both the nature of your data and the question you're trying to answer.



scikit-learn algorithm cheat-sheet



Choose your Suitable ML Model

- Know your data
- Clean your data
- Augment your data
- Categorize the problem
- Understand your constraints
- Find the available algorithms

Q&A